Information Feedback and Learning in Construction Bidding

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Abstract

Information feedback in recurrent construction bidding is an important variable in optimal procurement design. Contractors tend to optimize their bids in recurrent bidding with positive reviews of historic bids. Our experiment examines the effects of no and partial information feedback on the bidding trends of (inexperienced) student bidders', and the extent to which their bidding tends to agree with the behavioural patterns proposed by learning theory. The results show that the variations in bids over time for both information feedback levels are statistically significant. Although the bidders with partial bidding feedback are more likely to vary their bids as indicated by learning theory, their bids are less competitive than those with no bidding feedback information. Construction clients would need to consider the information feedback in their procurement of construction services to achieve efficiency in construction bidding.

Keywords: Bidding, Experiment, Feedback, Learning

Introduction

Generally, construction procurement practices are a matter of choice for both public and private sector clients. One particular procurement policy that may affect competition in descending first-price sealed-bid construction bidding (i.e. lowest bidder wins at the lowest price) is the availability of information about bids submitted in preceding bidding competitions. Although the level of feedback information on historic bids varies across clients, in many cases, clients do not provide feedback information or provide insufficient feedback to contractors (Drew and Fellows 1996). Ockenfels and Selten (2005) claim that information feedback in repeated auctions is an important design variable in optimal procurement design, since it can substantially affect outcomes, even when the feedback has no strategic information value. At worst, irrelevant bidding feedback information can be ignored by the bidders. It follows that information never has a negative value to the decision-maker (Milgrom and Weber 1982).

There is a large number of studies in the conventional economics literature that have used experiments to explore the effects of information feedback in sealed-bid auctions. They provide a substantial amount of evidence that varying information feedback affect bidders' competitiveness to different degrees in sealed-bid auctions, thereby affecting the revenues of those accepting bids to buy or sell (e.g. Issac and Walker 1985; Dufwenberg and Gneezy 2002; Engelbrecht-Wiggans and Katok 2008). In the context of construction auctions, only recently Soo and Oo (2010) examined the effects of two information feedback conditions (full and partial) on student (inexperienced) bidders' bidding behaviour in an experiment. Over the eight bidding rounds in their experiment, they found that the variations in bids over time for full information feedback are statistically significant, but not for bids from bidders with partial bidding feedback. Also, bidders with full bidding feedback are more competitive than those with partial bidding feedback. If such evidence is found to be robust, it has important policy implications for construction clients' procurement practices. However, the state of knowledge in this area remains woefully inadequate, and more research is needed.

In this paper, we investigate the effects of no and partial information feedback on construction bidding. Our study overlaps with Soo and Oo (2010) on the partial information treatment, and the results should be viewed as complementary. The experiment of the present paper is analogous to that of Soo and Oo, with the following differences. First, the reported experiment was extended to ten rounds rather than eight and therefore provides additional insight into learning in recurrent bidding. Second, there were only four rather than five bidders. In addition, the investigation of learning effects in the paper proceeds along a different dimension. To theoretically explain the observations, it examines the extent to which the subjects' bidding trends agree with the behavioural patterns proposed by learning direction theory in Selten and Stoecker (1986) and Selten and Buchta (1999).

Information Feedback Conditions

The information feedback adopted by construction clients in sealed bid auctions can be broadly classified into full, limited and no information. In the full information feedback condition, bidders were informed at the end of each auction about all bids and the identity of the bidder making each bid. In the partial information feedback condition, bidders were provided only with the winning bid and the identity of the winning bidder at the end of each auction. These two information feedback conditions are more common among public sector clients that must maintain public accountability. For example, while the Government in Singapore adopts full information feedback in their public procurement (see www.gebiz.gov.sg), many government agencies opt for partial information feedback only (e.g. public agencies in Hong Kong, Malaysia, and Australia). No information feedback, on the other hand, is prevalent in private sector procurement of construction services. The high degree of post-bid negotiation in private sector procurement may explain the clients' unwillingness to provide feedback information to bidders. Nonetheless, Drew and Fellows (1996) detected that contractors in their survey obtained historic bidding data from a variety of sources, including: competitors, subcontractors, friendly acquaintances, suppliers and newspaper.

Although the above information feedback conditions have been found to elicit behavioural effects among bidders, the experimental findings in the economics literature seem to be mixed. It is also noted that the experiments on sealed bid auctions were designed in different settings, namely predominantly ascending first-price sealed-bid auction (i.e. highest bidder wins at the highest price) as compared to this experiment with descending first-price sealed-bid auction (i.e. lowest bidder wins at the lowest price). For example, the classic paper by Isaac and Walker (1985) found that the bid prices in partial feedback condition are higher than those generated in full feedback condition in ascending sealed bid auctions with four bidders, thereby raising the revenues for those agents accepting bids or accepting offers. More recently, Neugebauer and Perote (2008) examine the order effect of feedback information in bidding behaviour. They ran the experiment in both orders: no-to-partial information order and the reverse, partial-to-no information order. Their findings suggest significant order effect and the feedback information on winning bids triggers an immediate response in bidding behaviour, leading to higher overall bid prices. Dufwenberg and Gneezy (2002), in a descending sealed-bid auction, compare three levels of information feedback and conclude that full information feedback leads to higher bid prices compared to partial and no information feedback. Other studies that provide overviews of experimental studies on the effects of feedback information include Ockenfels and Selten (2005), and Neugebauer and Selten (2006).

Learning in Construction Bidding

According to Drew and Fellows (1996), contractors use feedback on historic bids for four different purposes: (i) for deciding on whether or not to bid for future projects, (ii) for determining mark-up for future projects, (iii) for analysing their bidding performance; and (iv) for analysing bidding performance of their competitors. In competitor analysis, information on

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historic bids could be used to estimate the probable range of competitors' bids, and to differentiate the less serious competitors from the more serious, thus allowing a contractor concerned with bidding strategies to target key competitors (Oo et al. 2010). Fu et al. (2002) suggest that bidders tend to optimize their bids in recurrent construction bidding process with positive reviews of previous bidding results, suggesting feedback plays a key role within the experiential learning process in bidding (i.e. learning from experience, see Kolb (1984)). They found that experienced contractors who bid more frequently submitted more competitive bids than contractors who bid only occasionally. A conceptual framework of learning in recurrent construction bidding was proposed in Fu et al. (2004) in which a contracting firm is seen as an interpretation system. The learning process activates the interpretation process that transforms a flow of data (i.e. previous bidding results and data derived from completed and ongoing projects) into information, and that interpreted information is incorporated into next bidding decision to enhance competitiveness. In their examination of a bidding dataset covering six years, there is evidence of behavioural regularity among experienced contractors when an optimal bidding strategy has been reached in what they refer to as steady-state learning phase in recurrent construction bidding. However, their analysis only partially supports the existence of rapid learning during the start-up phase among inexperienced contractors.

In an attempt to link observed sensitivity of bids to information feedback, a learning direction theory in repeated first-price sealed-bid auction has been proposed by Selten and Stoecker (1986) and Selten and Buchta (1999). Learning direction theory is a qualitative behavioural theory about learning in repetitive decision tasks. As an illustration of the theory, Selten and Buchta (1999) used an example of a marksman who tries to hit a trunk. If the arrow misses the trunk to one side the marksman shifts the bow in the direction of the other side when he gives it another try. The behaviour of the marksman in the example is based on a qualitative causal relationship: if he misses to the right, for instance, then he tends to aim more to the left. This line of reasoning links to ex-post rationality, one looks at what could have been better last time and makes qualitative adjustment (i.e. the direction of the change rather than its size) in this direction, in which the right kind of feedback plays a key role therein. This theory has been supported by the data of diverse experiments (for a review, see Selten 2004). In Neugebauer and Selten's (2006) experiment, for example, 92% of their experiment subjects conformed to the behavioural patterns proposed by learning direction theory. It is noted that a possible quantification of learning direction theory using impulse balance theory to account for different information feedback conditions has also been proposed in Selten et al. (2005) and Neugebauer and Selten (2006). In principle, the impulse balance theory weighs the foregone payoff upon losing against the foregone payoff upon winning, in which the impulse balance point is the bid where the probability of weighted foregone payoffs from losing and winning are equal. However, only the idea of learning direction theory is applicable to the experiment of the present paper. We examine the extent to which the subjects' bidding trends agree with the behavioural patterns proposed by the theory in the experiment.

Experimental Design

The experiment was conducted at the University Sains Malaysia between August and November 2010. The design used between-subjects variation and involved information feedback as the treatment variable. In total, all eighteen final year students in the Quantity Surveying degree participated in the experiment. The use of student subjects is appropriate in an experiment for which the level of experience is not a moderator variable (i.e. the level of experience is controlled - inexperienced bidders). The student subjects were randomly assigned to one of two treatments with ten bidding rounds (one round per week) per treatment. Each of the two primary groups were further split into four subgroups (two to three students in each subgroup) to emulate a bidding competition of four competing bidders. In treatment P (partial information feedback), subjects were provided the winning bid and the identity of the winning bidder in the preceding round at the beginning of each bidding round.

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In treatment N (no information feedback), subjects received no information about previous bids (i.e. winning and losing bids).

In weekly meetings (between 30 – 60 minutes), the groups were given a list of six hypothetical projects and the subjects were required to decide which project to bid for, and the bid price if deciding to bid. The general instruction to the subjects was that their ultimate aim was to survive and prosper in a competition where the lowest bidder wins the job, but how this can be achieved was left to them. This reflects the strategic nature of the construction pricing problem. The sixty hypothetical projects were conventional buildings, such as schools and institutional buildings that involve conventional designs, and do not require any unusual construction technologies. This was done to control the effect of project type on bidders' bidding decisions. Apart from the project information (location, duration, client and contract type), the subjects were also given an unbiased cost estimate for each hypothetical project, which is the net project construction cost that includes site overheads and project preliminaries (i.e., total of direct cost estimate + site overheads). Here, identical hypothetical projects were given to both treatment P and N groups to enable direct comparisons.

In an attempt to make the experiment more realistic and to maintain the subjects' interests over ten rounds, it was conducted in an environment in which experiences (learning) could be gained and bankruptcy could occur. Each subject was given a start-up capital of RM 400,000[1] to sustain the operating expenses (capital charges, general overheads, etc.) estimated at RM 40,000 per bidding round, and profit/loss was generated for each hypothetical project they won in the experiment. The profit/loss was determined by deducting a randomly assigned final cost (ranging from 90% to 110% of unbiased cost estimate) from the winning bid. In this way, subject whose losses exhausted their start-up capital and profit gained from projects would be declared bankrupt and no longer allowed to bid. Similarly, failure to win job to pay for operating expenses (fixed costs such as capital charges, general overheads, etc.) would eventually force the group out of the 'market'- a reality in the 'real' construction industry. Also, the subjects have limited working capacity and would have incurred a cost penalty (for the added costs of securing additional resources) if they had to operate beyond their optimal capacity (maximum five projects on hand at a time). After each round, subjects in both treatments were informed privately of their capacity utilization and the profit/loss generated from the projects they won in previous rounds. The subject that generated the biggest profit in the respective treatment at the end of the experiment was declared the winner and received a mystery prize (i.e., a prescribed textbook for their course).

Although the practicality of an experimental approach in construction bidding research has been demonstrated in previous studies (e.g. Dyer et al. 1989; Drew and Skitmore 2006, Oo et al. 2007, 2008), the quality of experimental data is obviously related to subjects' seriousness when bidding in the experiment. Therefore, for every project for which the subjects decided to bid, they were asked to indicate the estimated chance of winning with their bid. This provided a means for gauging their seriousness using a correlation test. In addition, after each round, the subjects were asked to indicate how they used the feedback in formulating their bidding strategies. At the end of the experiment, the following questions were also asked:

- How did you learn and improve your bidding performance?
- How long did it take to learn about the bidding trends of your competitors?

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[1] MYR 1 = AUD 0.355 or EUR 0.248 at the time of the experiment. MYR 400 000 is approximately AUD 140 000

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Experimental Results

The unbiased cost estimate provides a common baseline from which to measure the subjects' competitiveness and for comparing bids between two treatment groups. Correspondingly, the two measures of competitiveness between bids adopted in the analysis are given below:

$$BCP = 100 \, (x_i - x)/ \, x \qquad \text{(Eq. 1)}$$

where BCP is the bid competitiveness percentage, x_i is the ith subject's bid and x is the value of lowest (winning) bid entered for a project. Lower BCP indicates greater competitiveness and vice versa, with minimum and maximum competitiveness being constrained between infinity and zero, respectively.

$$MUCR = x_i \, / \, x \qquad \text{(Eq. 2)}$$

where MUCR is the mark-up competitiveness ratio, x_i is the ith subject's bid and x is the unbiased cost estimate for a project. A MUCR of 1 indicates that a bid is at the unbiased cost estimate (i.e., zero mark-up), and below 1 indicates a bidder has submitted a bid lower than the unbiased cost estimate that leads to a lower bid. Lower MUCR values indicate greater competitiveness since the lowest bidder wins at the lowest bid price. Consistency in bidding can be gauged from the resultant standard deviation.

Subject ID	No. of bidding attempts	No. of winning bids	Average mark-up %	Average BCP	S.D. of BCP	Bidding success rate (%)	Market share (%)	Profit/loss ($)
Partial information feedback group (treatment P)								
A1	60	28	7.29	3.33	5.96	46.67	43.73	2,647,900.99
A2	58	3	11.34	7.69	7.28	5.17	5.53	1,592,900.00
A3	47	13	7.51	4.40	3.58	27.66	22.57	3,299,650.00
A4	46	16	4.49	1.84	2.47	34.78	28.18	3,425,394.00
No information feedback group (treatment N)								
B1	38	22	4.22	1.36	2.97	57.89	40.45	2,739,350.00
B2	36	21	4.68	1.83	3.30	58.33	33.40	2,790,550.00
B3	49	6	5.72	2.52	1.81	12.24	8.83	808,450.00
B4	60	11	4.93	1.71	1.38	18.33	17.32	2,066,700.00

Table 1 The breakdown of bid data according to experimental treatment

Table 1 shows the breakdown of the bidding data from both treatment groups. A total of 211 and 183 bids were obtained from treatments P (Subjects A1 to A4) and N (Subjects B1 to B4), respectively. The range of average mark-up % applied to the unbiased cost estimate varied between 4.49 and 11.34 for treatment P, while a lower range between 4.22 and 5.72 was recorded in treatment N. A further examination of the dataset revealed the presence of three outliers (i.e. bids that are 25% above the winning bid) in treatment P, which may explain its variations in average mark-up %. These outliers were removed in subsequent statistical tests. The bidding performance of individual subjects is further examined in terms of number of winning bids, average mark-up %, average BCP, bidding success rate, market share and profit/loss. It is interesting to note that the winners (i.e. Subjects A4 and B2) recorded the lowest number of bidding attempts in their respective treatment group, suggesting they were selective in their bid/no-bid decision. Also, they are very close to each

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other in terms of their average mark-up% (4.49% and 4.68%) and average BCP (1.84% and 1.83%), even with different treatments.

Seriousness of Bidding

We begin the statistical analysis of the bidding dataset with a test on the subjects' seriousness of bidding. Notwithstanding the experimental treatment, if a subject has submitted a serious bid (i.e. with low mark-up %), it follows that the corresponding estimated chance of winning should be high and vice versa. The Pearson Correlation coefficient between the subjects' mark-up % and their estimated chances of winning has the expected negative sign, $r = -0.072$, significant at $p < 0.10$ level. This would indicate that the subjects had bid seriously in the experiment. However, the correlation is rather weak. A further examination on the dataset shows that the corresponding correlations are -0.164 ($p < 0.05$) and 0.032 ($p > 0.05$) for the bids from Round 1 to 5 and 6 to 10. Although the latter is not statistically significant, the presence of high bids which were associated with high estimate for chances of winning at the later stage of the experiment could possibly due to the fact that, as the experiment proceeded, the relatively experienced subjects were more confident in their ability to win bids.

First Bids

It is especially interesting to examine the subjects' first bids because they were submitted before the subjects were exposed to different experimental treatments. In addition, no experience could be gained at this first bidding round. Using the 36 bids obtained in first bidding round, a Mann-Whitney U test was performed to test the difference in bidding competitiveness in terms of MUCR between the two treatment groups. The results show that the first bids from the two treatment groups do not differ significantly (U = 137.5; Z = -0.775; $p > 0.05$). This means that, in round 1, different experimental treatments in different groups do not influence the subjects' bidding behaviour.

Between Treatments Comparison

When comparing the development of the subjects' bids in later periods, the means of MUCR for the P and N treatment groups are 1.0732 and 1.0495, respectively. A Mann-Whitney U test shows that the difference is statistically significant (U = 13142.00; Z = -5.282; $p < 0.01$). This suggests that the bids from partial information feedback group are less competitive on average with a higher mean MUCR compared to those in the no feedback group. In addition, the standard deviation for the partial information feedback group is higher (i.e. 0.0494 as compared to 0.0321 in treatment N), indicating a lower degree of consistency in their bidding attempts. The higher average bids with lower consistency in the partial information feedback group is consistent with the subjects using the winning bid as a bench mark in their decision making as if it was the market price, in their attempts to maximize their profits.

To examine the bidding trends in P and N treatments, Figures 1(a) and 1 (b) plot the corresponding MUCR over the rounds of the experiment. LOWESS curves were fitted to the scatter plots to allow for bidding trends to be observed from the dataset. It can be seen that the mark-up for treatment P is continually decreasing over the ten bidding rounds, while it is rather flat from round 3 onwards in treatment N. These decreasing trends in MUCR provide a strong indication of continuous learning leading to more competitive bids generally over time. For treatment P, however, the mark-up decreases steadily moving from round 1 to round 8, in which the MUCR decreases from 1.12 in round 1 to 1.05 in round 8. Apparently, information about the winning bids is of great importance for subjects in treatment P. As revealed in the questionnaire, they were able to assess their bids relative to winning bids, and to review their performance and adjust their bidding strategies accordingly.

In treatment N, with no information about previous bids, the relatively flat bidding trend from round 3 onwards suggests a high consistency in bidding among the four subjects. However,

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it appears that the subjects had experienced a short adjustment phase from Round 1 to 2 as demonstrated by the steeply decreasing trend, before they were provided with feedback on profit or loss of the jobs they won in preceding rounds. The profit and loss statements provided to the subjects were not available until the end of Round 2 since the hypothetical projects have minimum project duration of two rounds. Indeed, the release of profit and loss statements did trigger an immediate response in the subjects' bidding trend, given the slight increase observed between Round 3 and 4. Further evidence of the upward adjustment can be found by considering the mean ranks of MUCR in the subsequent subseries analysis on changes in bidding (Table 2).
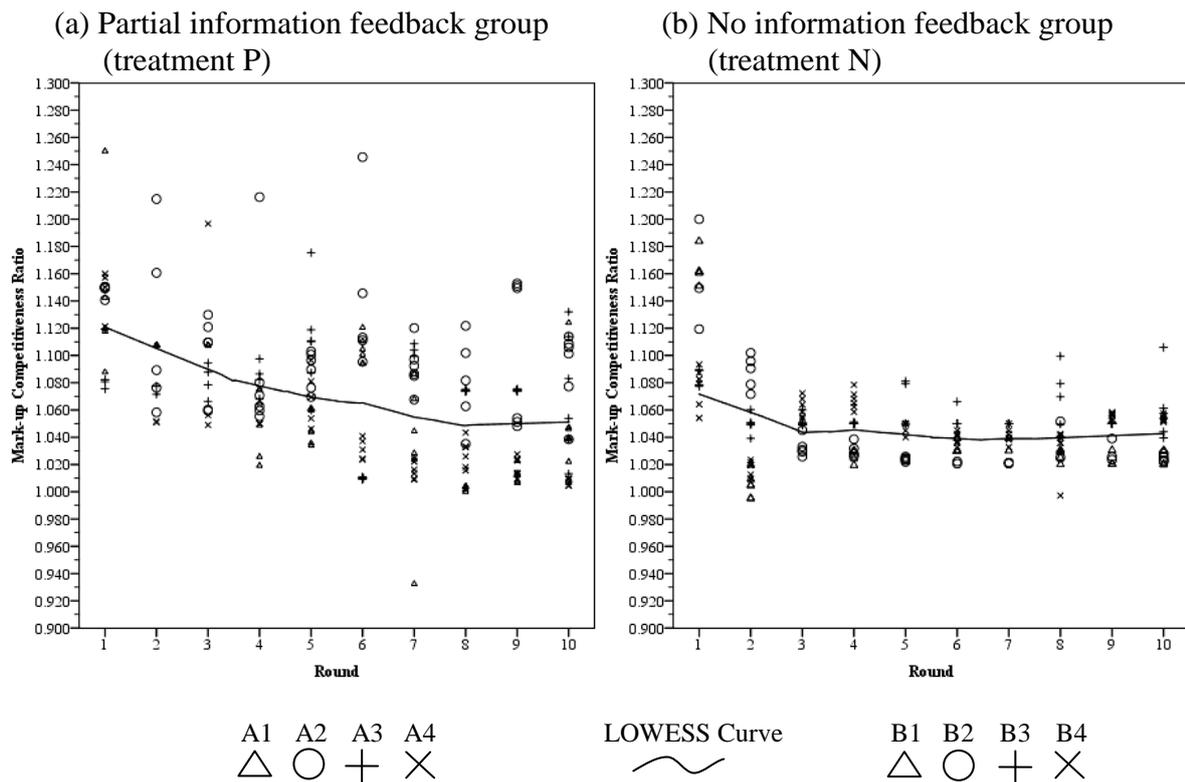

Figure 1 MUCR scatter plots for partial and no information feedback groups

Round Subseries	Mean Rank	N	Chi-Square	df	p
Partial information feedback group (treatment P)					
1 - 3	3.44	26	26.24	3	0.000
4 - 5	2.63				
6 - 7	2.27				
8 - 10	1.65				
No information feedback group (treatment N)					
1 - 2	2.13	23	9.63	3	0.022
3 - 4	3.17				
5 - 6	2.52				
7 - 10	2.17				

Table 2 Friedman test results for partial and no information feedback groups

From the LOWESS curves in Figures 1(a) and 1(b), it can be seen that there are disjointedness in bidding trends over the ten rounds of experiment. The disjointed trends in the respective LOWESS curve form subseries of bids for checking statistically differences in

bidding using a Friedman test. As shown in Table 2, there are four subseries of bids in treatments P and N, respectively. The mean ranks were calculated for all subseries (i.e. a higher mean rank indicates a higher MUCR overall) and the results show that there is a significant overall difference among the four mean ranks in both treatments P (χ^2 (3) = 26.24, $p < 0.01$) and N (χ^2 (3) = 9.63, $p < 0.05$). This suggests that the variations in bids over the bidding rounds in response to the experimental treatments are statistically significant. The subjects do apply different bidding strategies (mark-ups) based on the given set of feedback information, although the subjects in treatment N were only informed privately about their capacity utilization and the profit or loss generated from the projects they won in preceding rounds. In this, the mean rank of MUCR for Rounds 3 to 4 subseries is higher than the subsequent two subseries, suggesting they had adjusted their bids (i.e., with high mark-ups to maximize profit) in response to the information received at the end of Round 2.

Confirmation of Learning Direction Theory

In both treatment groups, it appears that learning does occur at different rates, with statistically significant variations in bids over the rounds of the experiment. The questionnaire survey reveals that the majority of the subjects learnt about the bidding trend by experimenting with their bids for improving their bidding performance. They were particularly concerned with the cost penalty for operating beyond the optimal capacity in their bidding decisions. The quoted period for learning about their competitors' bidding trends ranges from two to ten rounds of the experiment.

Consider now the application of learning direction theory to this experiment. As the subjects' ultimate aim is to win and make a profit, conditional on the allowable capacity utilization (maximum five projects on hand at any particular bidding round), it follows that the subjects would be in one of the following two conditions at the end of the preceding round:

High level of capacity utilization: number of projects on hand ≥ 3

Low level of capacity utilization: number of projects on hand < 3

where three projects on hand (the mid-point of five) were used as the cut-off point in determining the level of capacity utilization. A high level of capacity utilization means that a subject won a number of projects in the preceding round. This doesn't necessarily mean a high profit. He might have received a greater payoff by submitting higher bids and winning fewer contracts. Similarly, with a low level of capacity utilization the subject could have won more projects by submitting lower bids and winning more projects in the preceding round. Therefore, the learning direction theory implies that after experiencing a high level of capacity utilization a subject tends to increase his bids, while after experiencing a low level of capacity utilization the subject tends to decrease his bids.

Table 3 shows the number of bid changes in terms of mean MUCR, i.e., increases or decreases of the bids from one round to the next. Changes are listed separately according to the experimental treatment and the subjects' condition of high or low level of capacity utilization in the preceding round. A first observation reveals that in 100% of the observations there was an increase or decrease from one bidding round to the following, suggesting the subjects had in general adjusted their mark-ups. In treatment P, the bid changes that go in the predicted directions after experiencing high and low levels of capacity utilization are about 60% and 80%, respectively. However, the corresponding percentages in treatment N are only about 40% and 65%. This suggests that bid changes in the predicted direction occurred less often in treatment N. A Chi-Square test of independence was performed to examine the relationship between bid change and experience condition in the respective treatment. The results show that the relationship is significant in treatment P (χ^2 (1) = 5.386, $p < 0.05$), but not in treatment N (χ^2 (1) = 0.125, $p > 0.05$). The test statistic provides further evidence that the subjects in treatment N were less likely to vary their bids as indicated by

learning direction theory than were those in treatment P. In both experience conditions, a subject in treatment N had limited information whether he could have performed better than preceding round by increasing or decreasing his bids; in hindsight, the subject did not receive information on historic bids.

Treatment	Experience condition	Mean MUCR increase (%)		Mean MUCR decrease (%)		Row total (%)	
P	≥ 3 jobs on hand	10	(59)	7	(41)	17	(47)
	< 3 jobs on hand	4	(21)	15	(79)	19	(53)
N	≥ 3 jobs on hand	7	(41)	10	(59)	17	(50)
	< 3 jobs on hand	6	(35)	11	(65)	17	(50)
Column total (%)		27	(39)	43	(61)	70	(100)

Table 3 Frequencies of bid changes in rounds 2-10

Discussion

The insignificant difference in first bids between the two treatment groups provides evidence that the student subjects' level of experience is not a moderator variable in the experiment. That is, the level of experience is controlled – they were all inexperienced bidders before the experiment. In addition, the quality of the experimental data has been demonstrated as the test results show the seriousness of the subjects' bidding, which justifies the use of student subjects in this kind of experiment. It should be noted that the use of student subjects is very common in experimental auctions and business decision making studies (e.g. Remus 1986, Depositario et. al 2009).

In contrast to Soo and Oo's (2010) experiment on full and partial information feedback that suggests the more limited the feedback the higher the bid prices, our results show that bids from the partial feedback group are higher on average than those in the no feedback group. This would be in line with another notion in which the more limited the feedback the lower the bid prices (Isaac and Walker 1985). These contrasting findings warrant further experimental studies in this area.

In examining the subjects' learning in the experiment it is apparent from the variations in the bids - the observed learning in treatment P - supports the conclusion that the release of the winning bids trigger an immediate response in bidding behaviour, similar to that found by Dufwenberg and Gneezy (2002). Indeed, the observed learning in both treatments P and N are in line with Neugebauer and Perote's (2008) findings that subjects learn to bid on the basis of winning bids when provided with this information, and reflect on their bids when information on winning bid is unavailable. In treatment N, it seems that the subjects learn to bid on the basis of repeated reflection on their bids, where fewer bids go in the direction predicted by learning direction theory. Despite this finding, it is clear that the learning direction theory has the potential to provide qualitative predictions about bidding trends, without a fully-fledged behavioural model. The basic principle of ex-post rationality in learning direction theory is also in line with the logic behind McCaffer and Pettitt's (1976) cusum curve that predicted changes in contractors' bids in response to need of work.

Conclusion

Information feedback is an important design variable in optimal construction procurement designs. Feedback plays a key role in contractors' learning process in recurrent construction bidding. Our experiment examined the effects of no and partial information feedback on construction bidding, and the extent to which inexperienced bidders' bidding trends agree with the behavioural patterns proposed by learning direction theory. The results show that the variations in bids over time for both levels of feedback are statistically significant. The bidders with partial bidding feedback are more likely to vary their bids as indicated by

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learning direction theory, but their bids are less competitive than those with no bidding feedback. The fact that different information feedback does elicit a statistically significant behavioural effect among bidders has implications for construction clients. They would need to consider the feedback in their procurement practices.

However, in order to determine the point at which feedback can be regarded as 'sufficient' to generate efficiency in construction bidding, exploration of pricing practice in response to different feedback conditions is required along three dimensions: empirical work on contractors' pricing regarding the three possible levels of feedback, empirical work on contractors' learning in decision making on pricing; and empirical work on order effects of feedback on contractors' bidding behaviour - moving from no-to-full information feedback condition and the reverse. The latter is of special importance for construction clients to examine the impacts of changes in policy on information feedback in their procurement practices.

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